Thesis Portfolio

Predicting Future Tumor Location in Patients with Brain Metastases

(Technical Report)

Criteria for Successful Integration of Machine Learning Tools in a Medical Setting

(STS Research Paper)

An Undergraduate Thesis

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Table of Contents

Sociotechnical Synthesis

Applications of machine learning have become increasingly prominent in everyday life, spanning across multiple fields. Today, machine learning is used in traffic prediction, computational finance, and has even shown promise in diagnosing breast cancer (Boyarshinov, n.d.; Ji et al., 2019; Rzeszótko & Nguyen, 2012). The STS portion of this paper defines criteria for the successful implementation of machine learning technologies within the medical field. The technical portion of this portfolio describes a machine learning approach for informing early detection of brain metastases. Therefore, the STS portion of the portfolio describes how the technology presented in the technical portion may be integrated into medical field so that its benefits may be realized.

The technical portion of this thesis aims to predict tumor formation prior to visualization using machine learning technologies. In order to complete this research, T2 contrast MRI data was collected from the University of Virginia Gamma Knife Radiosurgery Lab. These data sets included patients with multiple brain metastases, as well as others with no brain metastases. Due to the aggressiveness of the cancers GKS is intended to treat, for many patients imaging is available prior visualization of any specific metastasis. Metastasis volume was extracted from imaging prior to tumor visualization and compiled into a precancerous tissue data set. In contrast, this same approximate volume was extracted from the same relative location in a healthy brain and compiled into a healthy tissue data set. Both data sets were inputted into the existing neural network AlexNet to train the algorithm to detect healthy and precancerous tissue. The resulting system when presented with a new MRI image differentiates between healthy and precancerous tissue. Precancerous tissue is then flagged for future monitoring by oncologists. By flagging these areas, the hope is that metastasis can be detected prior to significant growth, and therefore, the amount of radiation necessary to treat the cancer and the risks associated with this treatment can be decreased significantly.

Machine learning technologies, such as that described above, has shown promise in improving patient care. However, to realize this benefit at a larger scale, machine learning technologies must be successfully implemented in the field. Four major questions are addressed to determine the steps necessary for successful implementation: Who is affected by the technology? What factors effect individual acceptance of the technology over the current approach? What steps can be taken to ease integration of the technology? What are unintentional consequences of data collection by the technology? These questions are evaluated in the context of research organized by policy analysis, historical case studies, interviews with medical professionals, and discourse analysis. To guide research and asses the relationship between machine learning technologies and society, Actor-Network Theory, technological momentum, and the concept of a paradigm shift are utilized as STS frameworks. This paper defines specific criteria for successful implementation of machine learning technologies in a medical setting. Defining these criteria provides a structed system that allows for society to benefit from the utility these machine learning technologies provide. Additionally, the knowledge acquired while defining these criteria establishes a relationship between society and an emerging technology that can be utilized to inform future STS analysis.

Completion of this STS in conjunction with the technical research provided many interesting insights. First, it brought to light the team’s bias in favor of computational methods over physician assessment. No team member provided any cautiously technophobic commentary as to why we should be wary in continuing with the project. After researching how widespread technophobia is amongst individuals, it seemed strange that no team members expressed any concern, particularly on how this technology could distract oncologists from other issues occurring in the brain. Additionally, it was interesting to look at what unexpected potential impacts the information derived from the technology could have on patients. For example, it has been proposed that in the future disease risk derived from genomic studies could be used to adjust insurance rates, ultimately negatively impacting the patient (Nill et al., 2019). Could the identification of precancerous tissue have similar unforeseen impacts? What perhaps became most apparent throughout research, was the importance of combating a separation of patient from the data associated with them. On the technical side, while processing these large data sets, the humanity that was behind them began to fade away. However, the STS research helped to refocus the team on the greater goal of providing improved patient care and consider non-immediate risks. The STS portion also allowed the team to evaluate what steps would be necessary to actually get oncologists using the proposed technology. Using this information, the team was able to reassess what metrics should be used to stress the benefits of the technology and what instructions on its capabilities should be paired with it. By conducting this technical and STS research side by side, the deliverables necessary for the success of the technology were clarified, and the motivation of patient benefit behind the project was emphasized.

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